Joint Center for Satellite Data Assimilation Seminar
June 4, 2013
NCWCP, College Park, MD

Extracting maximum information from GOES-R ABI and GLM instruments in regional data assimilation applications to high-impact weather

Milija Zupanski
Senior Research Scientist
Cooperative Institute for Research in the Atmosphere
Colorado State University
[https://www.cira.colostate.edu/projects/ensemble/index.php]

Contributions and collaborations

Programs:
- GOES-R Risk Reduction
- JCSDA
- NASA Global Precipitation Mission (GPM)
- NSF Collaboration in Mathematical Geosciences (CMG)

People:
- Karina Apodaca (CIRA), Man Zhang (CIRA), Lous Grasso (CIRA), Mark DeMaria (NOAA/STAR), John Knaff (NOAA/STAR), Min-Jeong Kim (CIRA-NOAA/EMC)
- Jun Li (CIMSS, Univ. Wisconsin)
- Prof. I. M. Navon (Florida State University)
- Sara Zhang (NASA/GSFC), Arthur Hou (NASA/GSFC)

High-End Computing:
- NOAA S4 (SSEC, Univ. Wisconsin)
- NCAR CISL (Bluefire, Yellowstone)
- NASA (Pleiades)

Motivation-1: GOES-R Satellite

- **Geostationary Operational Environmental Satellite**

❑ Advanced Baseline Imager (ABI)
  - ✧ 16 spectral bands (Vis/WV/IR)
  - ✧ Resolution: 5-15 min, 0.5-2 km

❑ Geostationary Lightning Mapper (GLM)
  - ✧ Total lightning (in-cloud, cloud-to-ground)
  - ✧ Day and night detection
  - ✧ Resolution: 8 -14 km

❑ High-impact weather
❑ Precipitation (water vapor, clouds)
❑ Air pollution (dust, SO_2, O_3)
❑ Increased spatiotemporal resolution

Motivation-2: High-impact weather

- **Severe weather**
  - ✧ Thunderstorms
  - ✧ Tornadoes
  - ✧ Rainfall
  - ✧ Hail
  - ✧ Flash floods

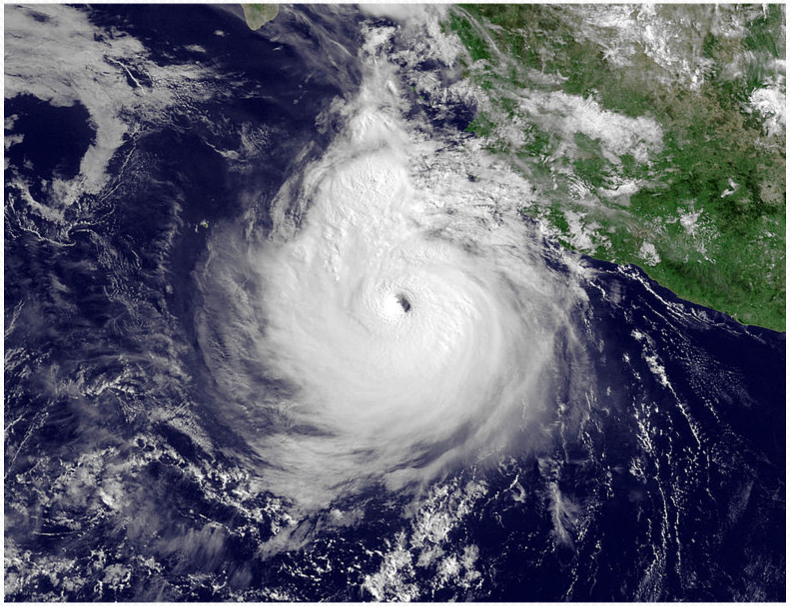
Mississippi tornado (04/2011)

- **Tropical cyclones**
  - ✧ High winds
  - ✧ Storm surge
  - ✧ Rainfall
  - ✧ Floods
  - ✧ Tornadoes
  - ✧ Rip currents

Hurricane Andrew (1992) - wind damage

Motivation-2: High-impact weather

- **Clouds: information to be utilized**
  - ✧ Typically associated with high impact weather
  - ✧ Can produce extreme rainfall and floods
  - ✧ High spatiotemporal resolution (microphysics)
  - ✧ Radiation



Hurricane Dora (2012) - GOES

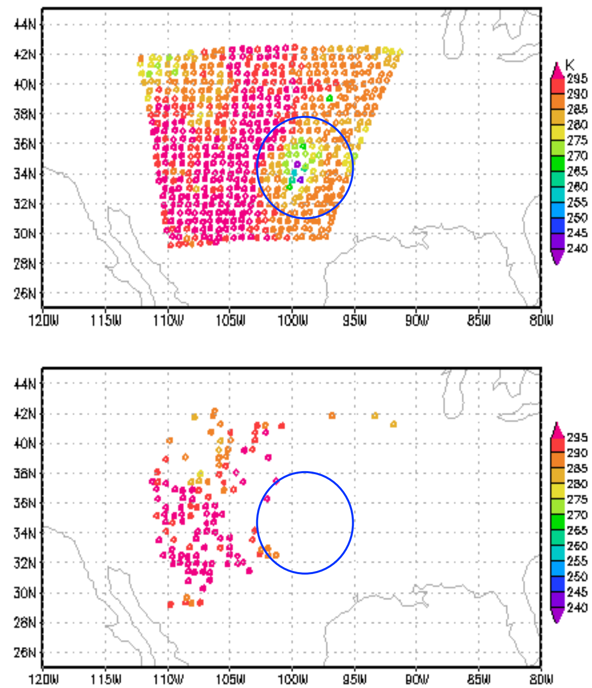
Supercell thunderstorm cloud (2010) - NASA

Improving analysis and prediction of clouds is challenging, but fundamentally important

Motivation-3: All-sky satellite radiance assimilation

- **Satellites observe clouds**
  - ✧ Visible, Water-vapor, Infrared, Microwave
- **Prediction of high impact weather relies on resolving cloud processes**
  - ✧ Cloud microphysics
  - ✧ Precipitation
- **Current operational weather prediction mostly relies on clear-sky radiance assimilation**
  - ✧ Simpler algorithm, computationally efficient
- **Observation of clouds can bring new information relevant for high-impact weather**
  - ✧ Constrain microphysics
  - ✧ Improved cloud representation benefits precipitation and radiation processes
  - ✧ Warn-on-forecast
  - ✧ TC track and intensity

Impact of cloud clearing



Re-development of the TS Erin (2007): Distribution of AMSU-B radiance data in the NCEP operational data stream: (a) all observations, (b) accepted observations after cloud clearing. Data are collected during the period 15-18Z, August 18, 2007. Note that almost all observations in the area of the storm got rejected by cloud clearing. (from Zupanski et al. 2011, *J. Hydrometeorology*)

Valuable information is lost due to cloud clearing

Satellite observations that can bring new information for high-impact weather

- **Microwave radiances**
  - penetrate clouds, can "see" inside
  - potential benefit for improving intensity of storms

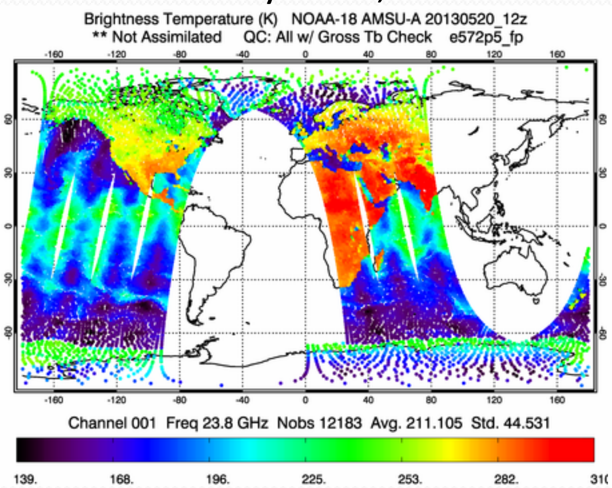
- **Infrared radiances**
  - imager cannot penetrate clouds, can "see" cloud tops
  - potential benefit for improving location of the storm

- **Spaceborne lightning**
  - indirect measurement of weather activity
  - location and intensity of storms

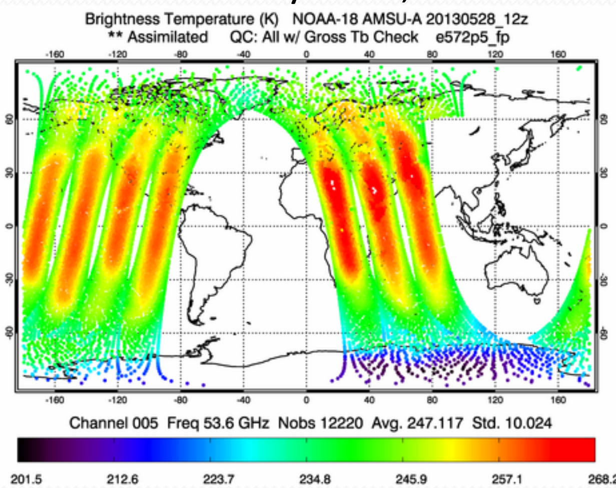
- **Spaceborne radars**
  - can penetrate clouds
  - high resolution

Microwave satellite information: AMSU-A

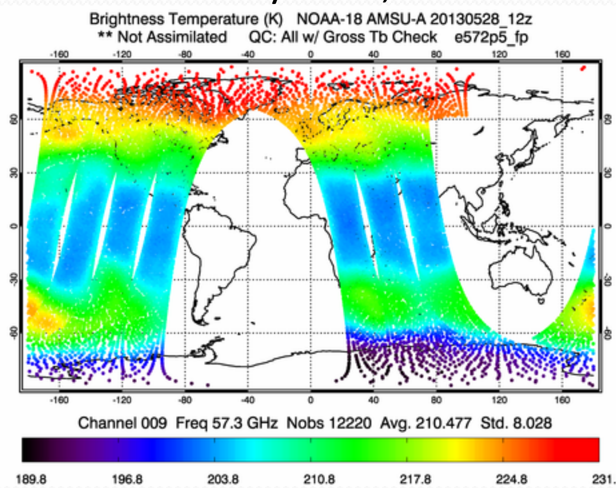
Channel 1: **23.8 GHz**
20 May 2013, 12z

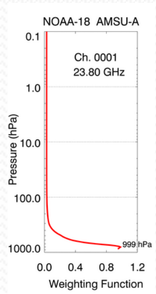


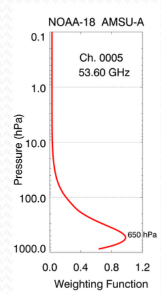
Channel 3: **53.6 GHz**
20 May 2013, 12z

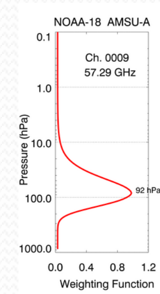


Channel 9: **57.3 GHz**
20 May 2013, 12z









Weighting function: **Surface**

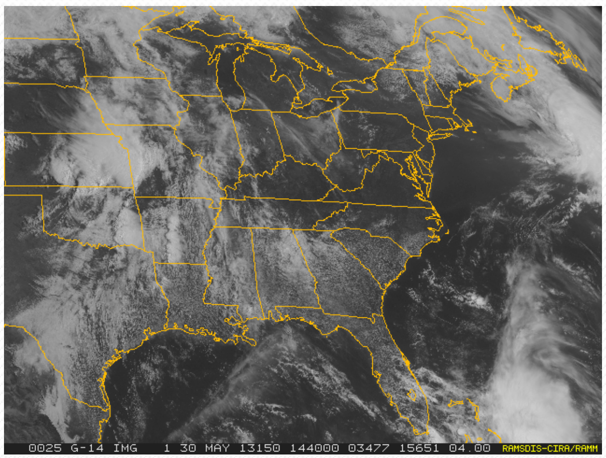
Weighting function: **650 hPa**

Weighting function: **92 hPa**

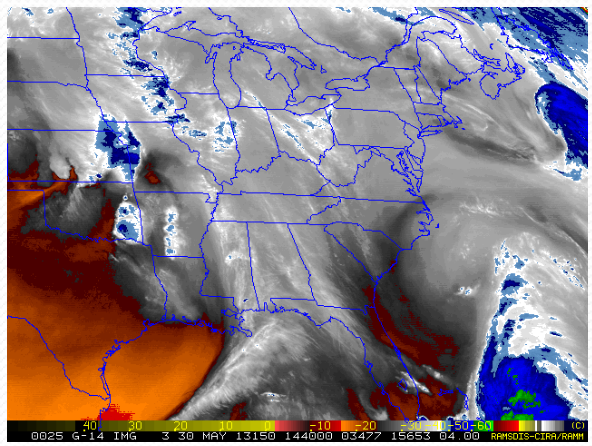
Complementary information from surface, lower and upper troposphere

Infrared satellite information: GOES-East

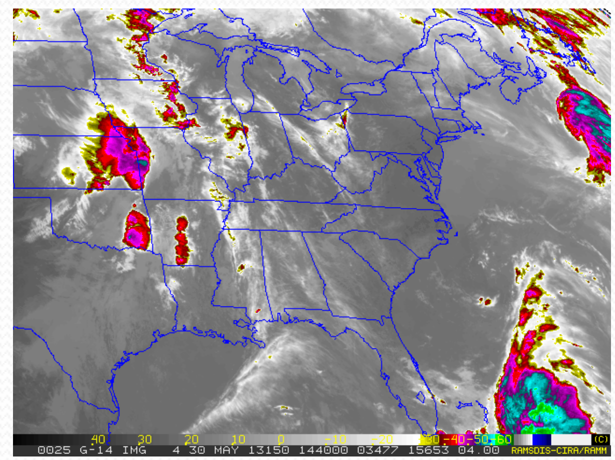
Visible (4 km)
30 May 2013, 13:15z



Water vapor (4 km)
30 May 2013, 13:15z



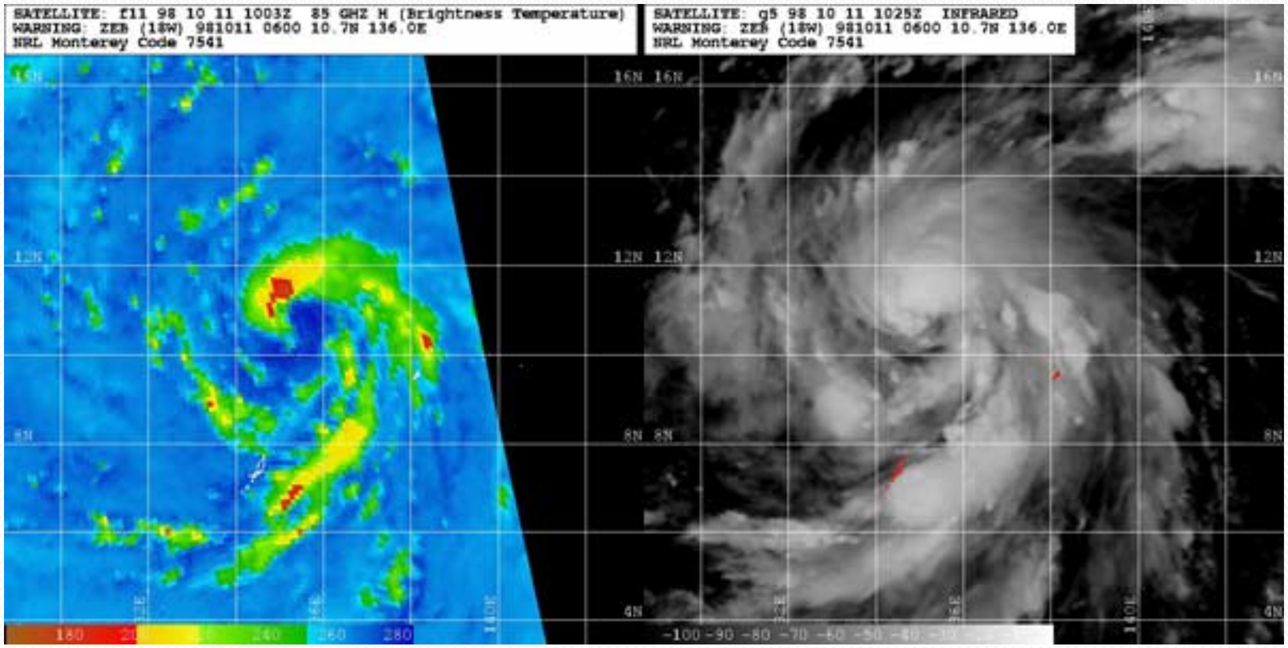
Thermal infrared (4 km)
30 May 2013, 13:15z



Additional information from multiple channels

Combined infrared and microwave

MW IR

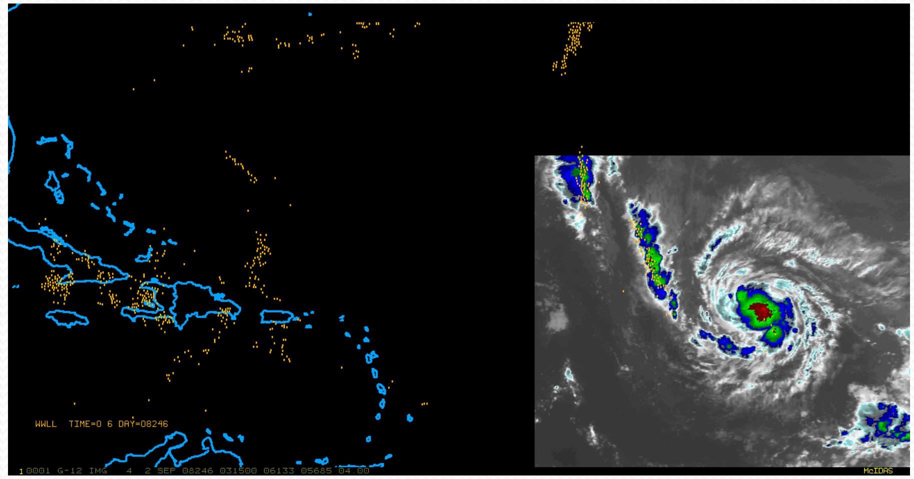


Typhoon Zeb (1998):
(**MW**) Dark blue marks a developing eye at the center of circulation. The greens and yellows in the spiral bands represent scattering signatures from precipitation-size ice particles above the freezing level.
(**IR**) Shows the Cirrus clouds and cumulonimbus that covers most of the storm. It shows a portion of the eye. However, the northern part of the eye is covered by cirrus clouds.

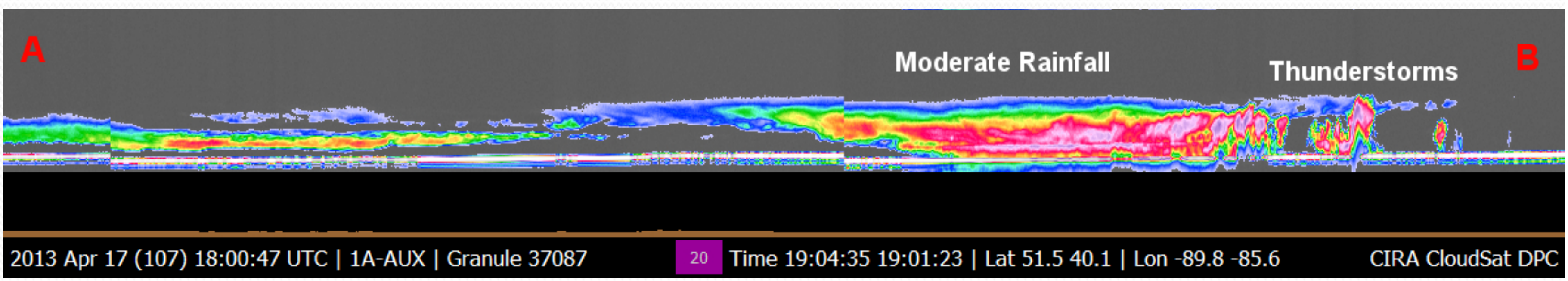
[Navy Research Lab Monterey, Marine Meteorology Division].

Lightning and radars

Lightning:
Hurricane Ike (2008)



CloudSat radar: Chicago flooding (April 2013)



Detailed information about the storm, clouds, and precipitation

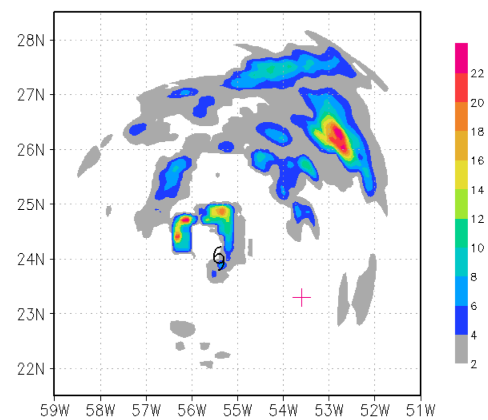
Challenges of all-sky satellite radiance assimilation for high-impact weather

- **Nonlinearity and non-differentiability**
  - ✧ Microphysical processes
  - ✧ Radiative Transfer (RT) model
- **Forecast error covariance**
  - ✧ Flow-dependent, cross-variable correlations, microphysics, dynamics
- **Bias correction**
  - ✧ Predictors for cloudy radiance bias correction
- **Computational limitations**
  - ✧ High-dimensional state vector for cloud-resolving data assimilation
  - ✧ Additional RT model calculations (e.g., scattering)
- **Other relevant issues**
  - ✧ Correlated observation errors
  - ✧ Non-Gaussian errors

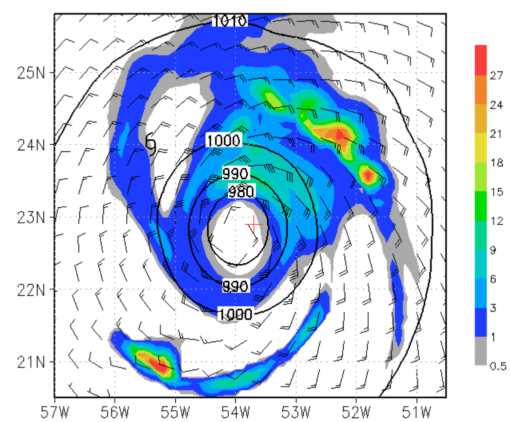
Nonlinearity: Impact of minimization in all-sky MW radiance DA: Hurricane Danielle (2010)

- Assimilation of AMSU-A all-sky radiances with NOAA HWRF-MLEF (9 km)
- TC circulation represented by total cloud condensate (g/kg)
- Solid lines represent the MSLP (hPa)
- DA cycle 8 valid 1200 UTC 26 August 2010

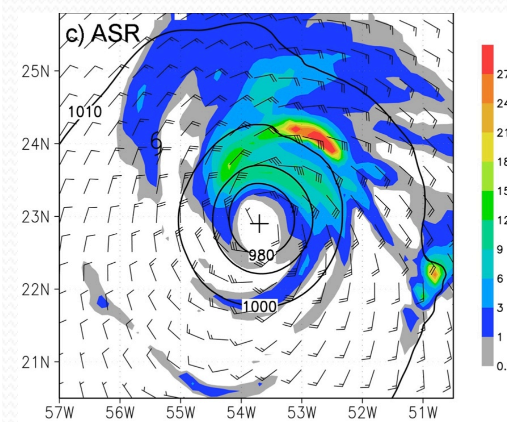
Precipitation rate (mm/h) at 1311 UTC 26 Aug 2010



One minimization iteration



Two minimization iterations



(from M. Zhang et al. 2013, *Mon. Wea. Rev.*)

Additional minimization iterations may be beneficial

Forecast error covariance

$$P_f = \begin{bmatrix} P_{dd} & P_{dc} \\ P_{dc}^T & P_{cc} \end{bmatrix}$$

P_{dd}: Correlations between **dynamical** variables

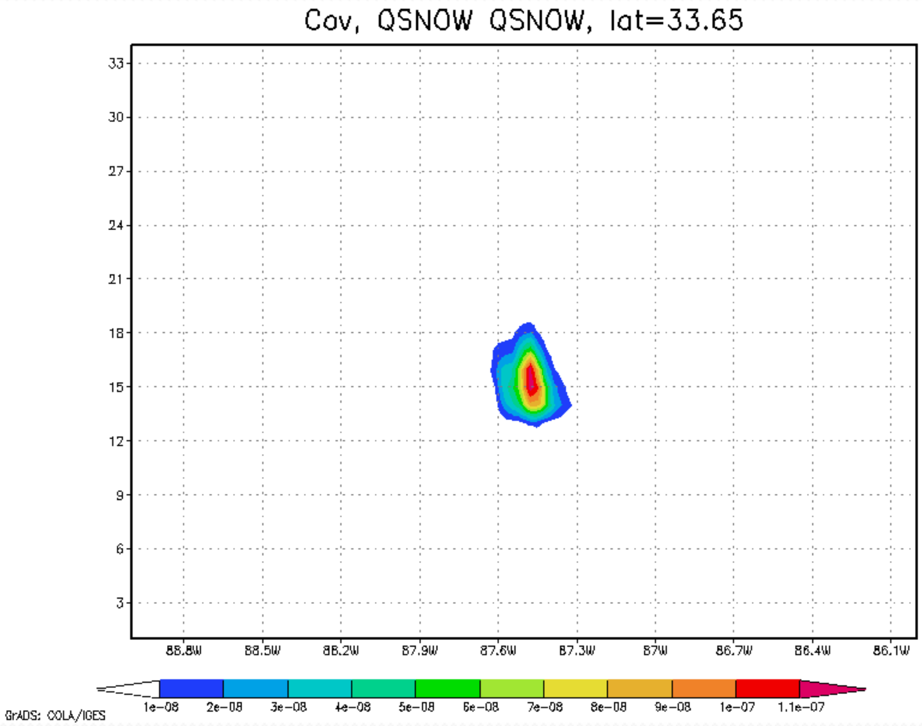
P_{cc}: Correlations between **cloud** (microphysical) variables

P_{dc}: Cross-correlations between **dynamical** and **cloud** variables

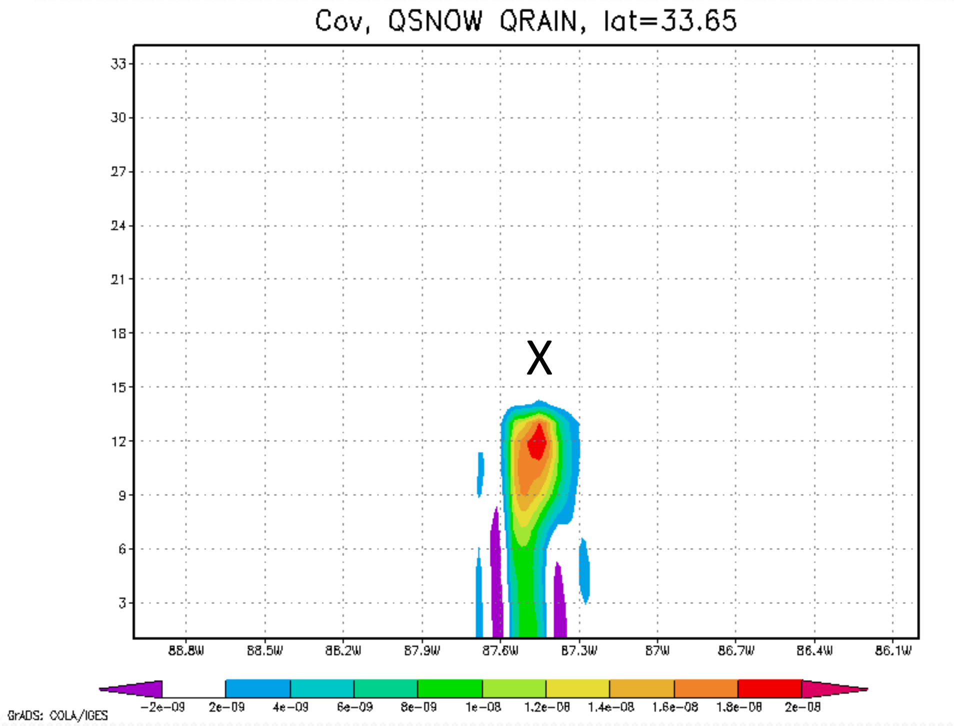
- Only P_{dd} is well known
- Correlations between microphysical variables not well known
- Even less known correlations between dynamical and microphysical variables

Single observation of cloud snow at 650 hPa: Vertical response

(a) Cloud snow at 34N



(b) Cloud rain at 34N



Flow-dependent and non-centered responses have to be created

Data assimilation algorithm: Maximum Likelihood Ensemble Filter (MLEF)

- A hybrid between EnKF and variational methods
  - iterative minimization (variational)
  - multiple realizations of model and observation operators for uncertainty (ensemble)
- Full-rank or reduced-rank
- Deterministic first guess forecast
- Analysis is the maximum of a posterior probability density function
- Nonlinear analysis solution by an iterative minimization
- Improved minimization efficiency by an implicit Hessian preconditioning

References:
Zupanski 2005 (*MWR*)
Zupanski et al. 2008 (*QJRMS*)

Generalization of Kalman Filter to include nonlinear model operators: MLEF Forecast

$$P_f^{1/2} = MP_a^{1/2} \quad \Rightarrow \quad \begin{bmatrix} p_1^f & p_2^f & \cdots & p_n^f \end{bmatrix} = \begin{bmatrix} Mp_1^a & Mp_2^a & \cdots & Mp_n^a \end{bmatrix}$$

- **In KF, the forecast error column is a forecast of the analysis error column**
- **Since** $\left\{ p_1^a \quad p_2^a \quad \cdots \quad p_n^a \right\}$ **spans the analysis uncertainty subspace, one can say that uncertainty is transported in time by a linear model** M

Generalize KF to include nonlinear forecast model:

Transport uncertainty in time by a *nonlinear* model $\mathcal{M}$

$$x^f = \mathcal{M}(x^a) \qquad x_i^f = \mathcal{M}(x^a + p_i^a)$$

$$p_i^f = x_i^f - x^f = \mathcal{M}(x^a + p_i^a) - \mathcal{M}(x^a)$$

Generalization of Kalman Filter to include nonlinear observation operators: MLEF Analysis

In standard KF, the analysis is obtained by minimizing a quadratic cost function
(i.e. linear observation operators)

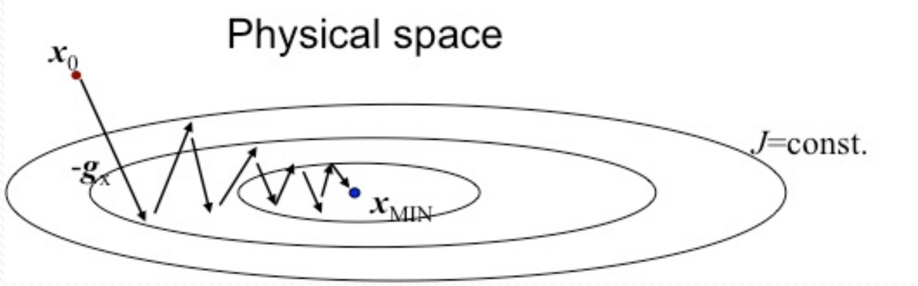
Generalize KF to include *nonlinear observation* operators:

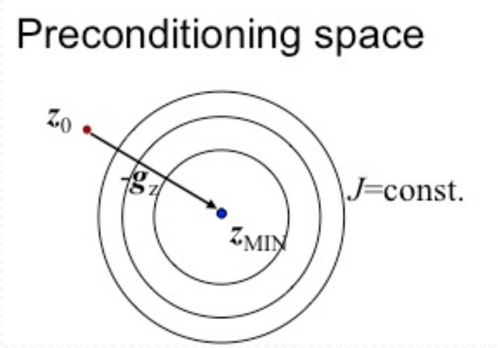
- Nonlinear observation operators require a robust and sophisticated minimization, so use the best applicable minimization method
- Since the minimization is critical, build data assimilation around minimization

$$J(x) = \frac{1}{2}\left(x - x^f\right)^T P_f^{-1}\left(x - x^f\right) + \frac{1}{2}\left(y - \mathcal{K}(x)\right)^T R^{-1}\left(y - \mathcal{K}(x)\right)$$

Why is Hessian preconditioning important?

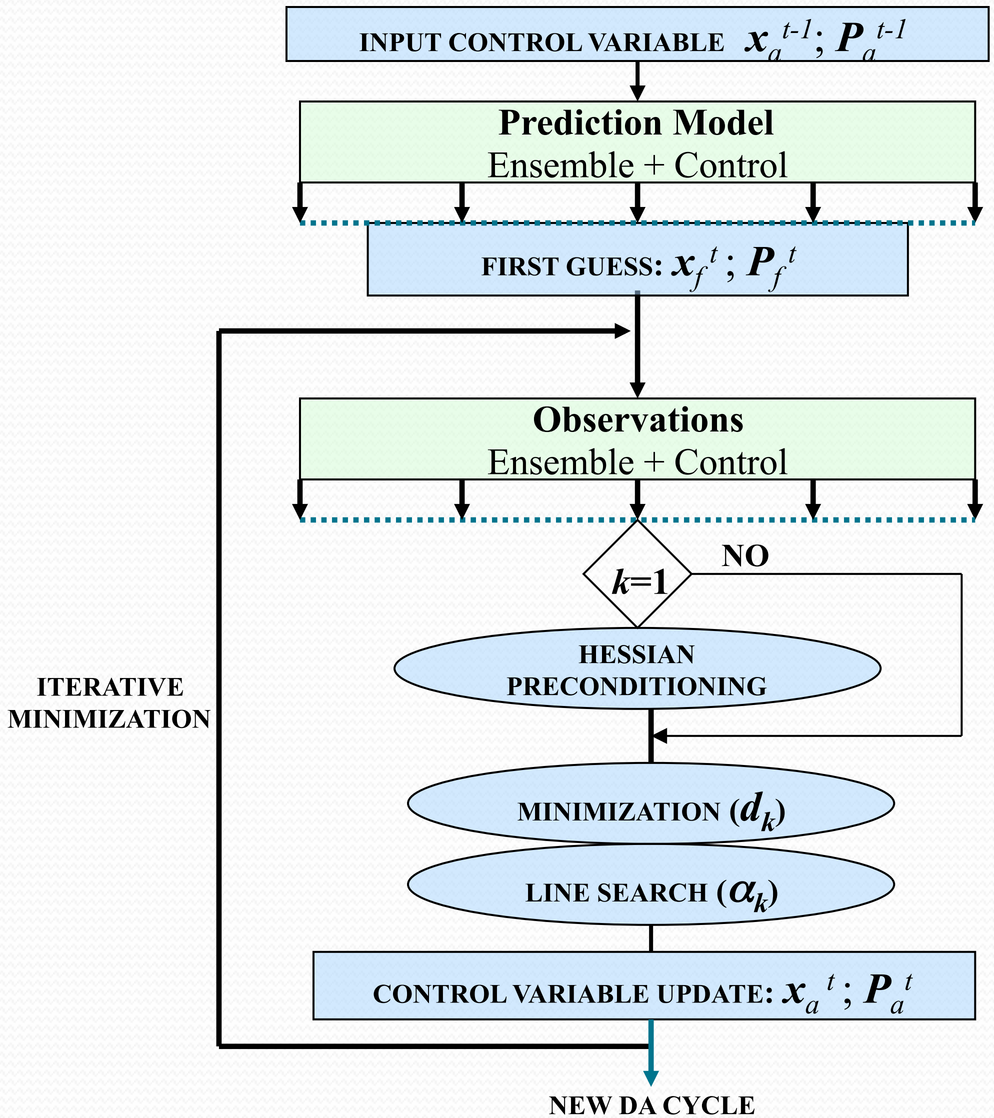
$$x - x_f = P_f^{1/2}(I + P_f^{T/2} K^T R^{-1} K P_f^{1/2})^{-1/2} z$$





- ❑ **Fast convergence from arbitrary initial state**
- ❑ **Impacts dynamical balance in multivariate DA**

MLEF flowchart



Modular MLEF

Observation module:
- Transform/interpolate from model to observations
- Read observations
- Output observation info: increments, errors, …

Forecast module:
- Import the forecasting system with pre- and post-processing
- Make *namelist.input* on-the-fly

Data assimilation module:
- Controls the processing of the model and observation info
- Hessian preconditioning, gradient, minimization iterations
- State vector and uncertainty estimates

Quantifying satellite information using Shannon information measures

Entropy

$$H\{X\} = -\int p(x)\log(p(x))\,dx$$

Change of entropy due to observations

$$\Delta H = H\{X\} - H\{X \mid Y\}$$

- Gaussian pdf greatly reduce the complexity since entropy is related to covariance

Change of entropy / degrees of freedom for signal (DFS)

$$\Delta H = DFS = trace\left[I - P_a P_f^{-1}\right]$$

In ensemble DA methods *DFS* can be computed exactly in ensemble subspace:

$$DFS = trace\left[(I + Z^T Z)^{-1} Z^T Z\right] \qquad Z = R^{-1/2} H P_f^{1/2} \qquad DFS = \sum_i \frac{\lambda_i^2}{1+\lambda_i^2}$$

Since eigenvalues of the matrix $Z^T Z$ are a by-product of assimilation, the flow-dependent *DFS* can be computed

All-sky microwave radiance assimilation: Tropical Cyclone Core applications

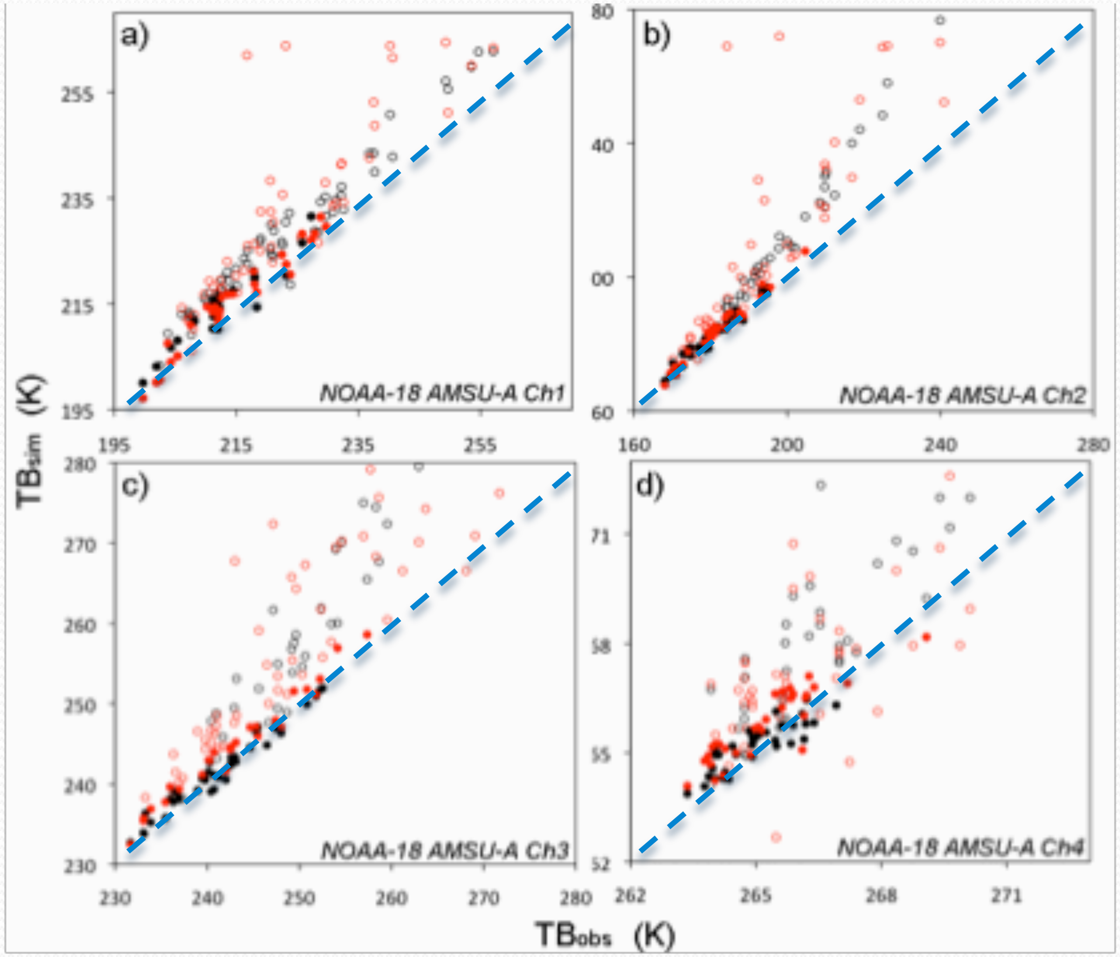
- **Model:** NOAA HWRF (operational in 2011, 27km/9km)
- **Results for TC core area (inner nest) at 9 km resolution**
- **Observations:** AMSU-A all-sky radiances, Channels 1-9 and 15 assimilated
- **Data assimilation interval:** 6 hours
- **Number of ensembles:** 32
- **Hurricane Daniele (2010)**
- **Bias correction from clear-sky GSI output**
- **From M. Zhang et al. (2013, *Mon. Wea. Rev.*)**

Radiance bias correction and quality control

CSR – clear-sky radiance
ASR – all-sky radiance

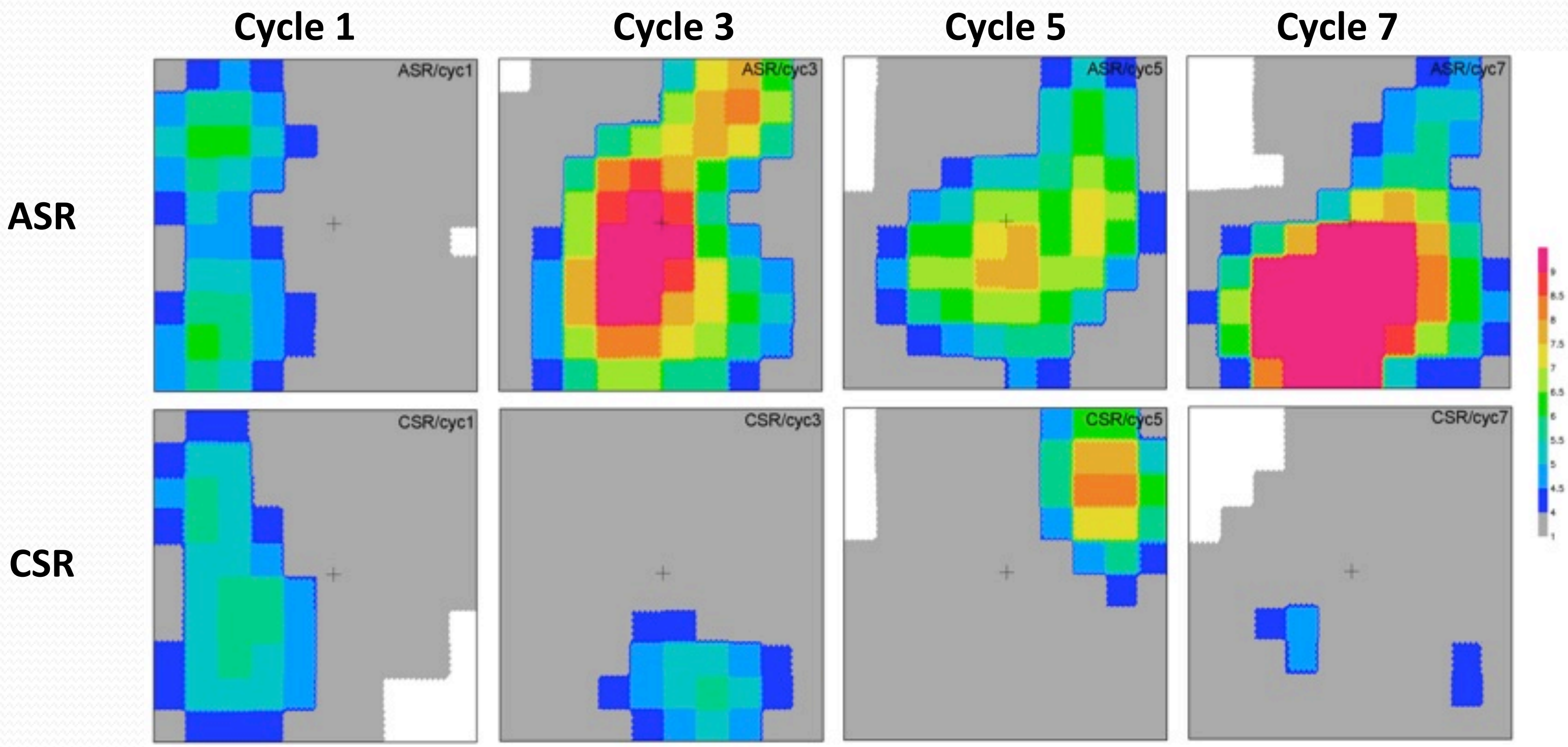
Before **quality control and bias correction**:
- ○ red circle: input ASR
- ○ black circle: input CSR

After **quality control and bias correction:**
- Red dot: assimilated ASR
- Black dot: assimilated CSR



Comparable TBs statistics after radiance bias correction and quality control

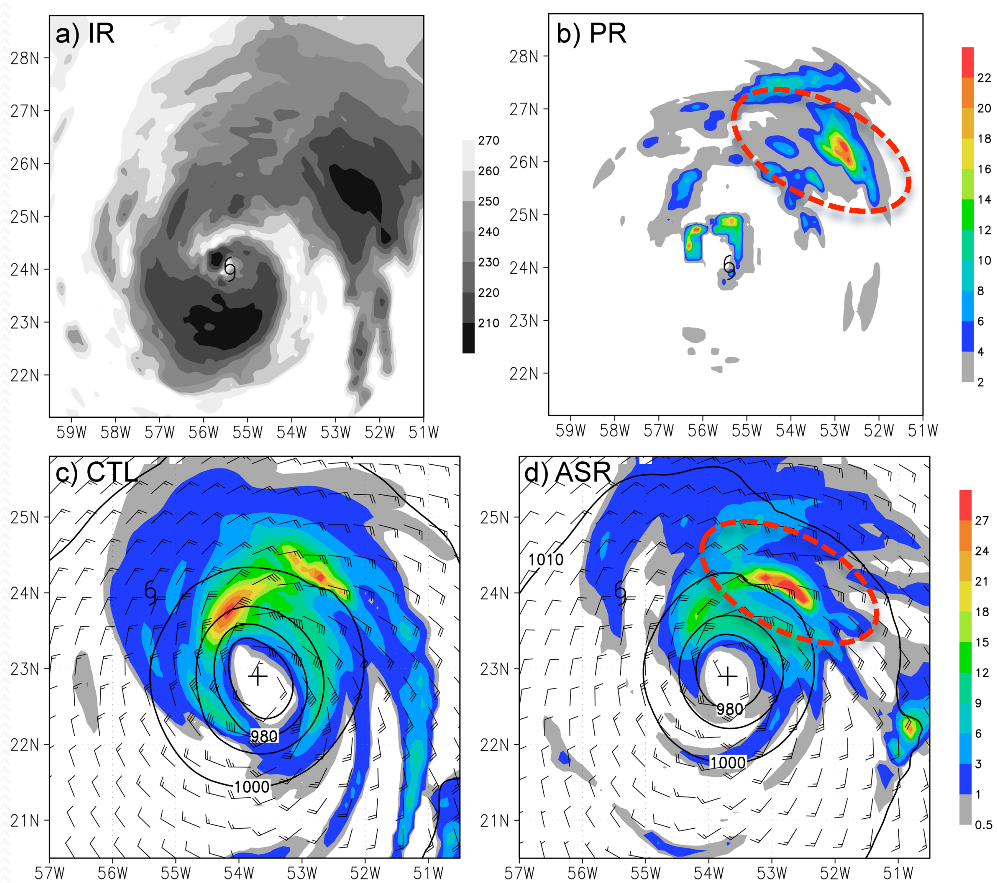
Hurricane Danielle (2010): All-sky AMSU-A information content (DFS)



Cloudy radiance observations add new information throughout the hurricane development

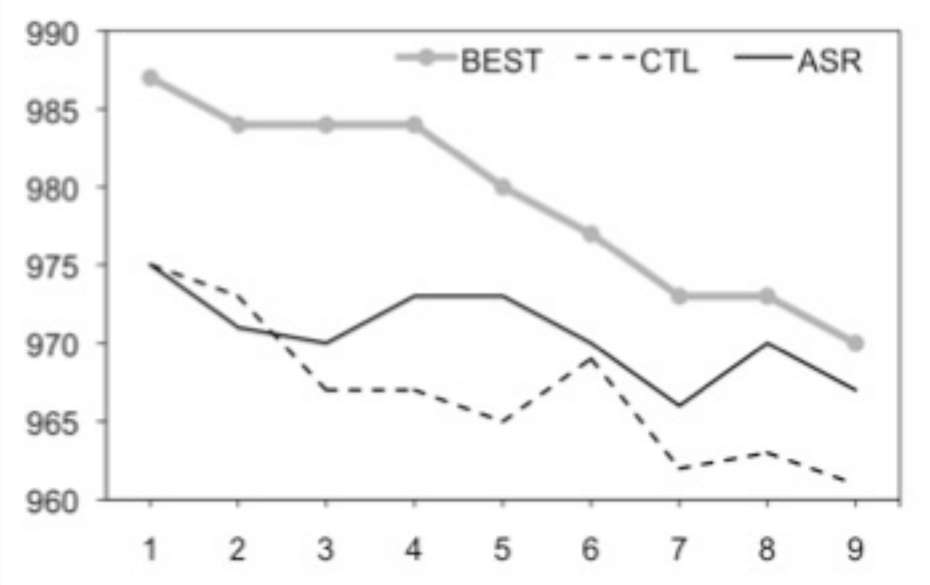
Hurricane Danielle (2010)

(a) IR imagery
(b) AMSU-A retrieved precipitation rate
(c) CTL – control experiment
(d) ASR – all-sky experiment



(a) Enhanced Infrared (IR) Imagery at 1145 UTC 26 Aug 2010 (Unit: K); (b) AMSU-retrieved precipitation rate map from MetOp-A at 1311 UTC 26 Aug 2010 (Unit: mm h-1). Distribution of the **6-h forecast** of the total cloud condensate (Colored; Unit: Kg m-2) at DA cycle 8: (c) the CTL experiment, and (d) the ASR experiment, superposed with mean sea-level pressure and 10-m above ground wind barbs from, valid at 1200 UTC 26 Aug 2010.

Hurricane Danielle (2010): Intensity



Hurricane Danielle (2010): Time series of the minimum sea level pressure (hPa) for NHC best track data (thick grey line) and MLEF-HWRF experiments ASR (solid) and CSR (dashed) between 1800 UTC 24 Aug and 1800 UTC 26 Aug 2010.

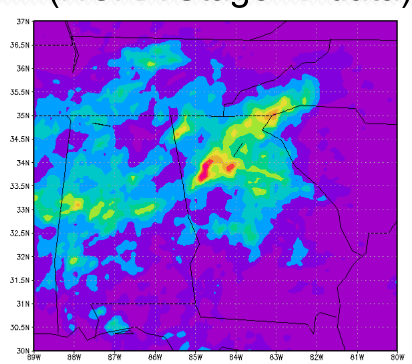
All-sky microwave radiance assimilation:

NASA Global Precipitation Mission - GPM: Downscaling satellite precipitation information using ensemble data assimilation (with Sara Zhang and Arthur Hou, NASA GSFC)

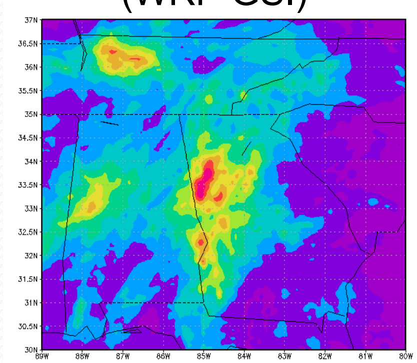
- Provide improved precipitation information for hydrology models
- Cloud-scale data assimilation with NASA WRF model (27-9-3 km)
- From S. Zhang et al. (2012, *Mon. Wea. Rev.*)

Surface precipitation short-term forecasts verification
(accumulated during 15-22 Sep 2009 in the southeast US flood region)

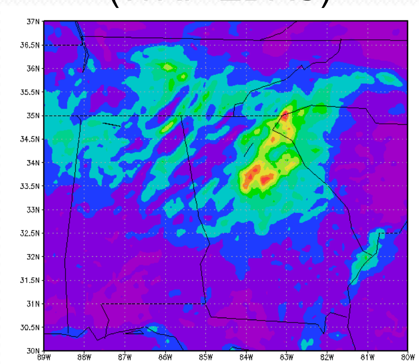
Ground-based Verification
(NOAA Stage IV data)



3DVAR, no AMSR-E,TMI
(WRF-GSI)



EDAS, with AMSR-E, TMI
(WRF-EDAS)



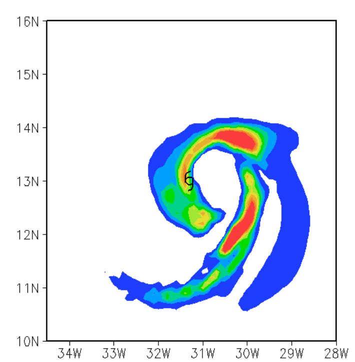
All-sky infrared radiance assimilation: Tropical Cyclone Core applications

- **Model:** NOAA HWRF (operational in 2011, 27km/9km)
- **Results for TC core area (inner nest) at 9 km resolution**
- **Observations:** SEVIRI all-sky radiances [10.8 μm - proxy for GOES-R ABI)
- **Data assimilation interval:** 1 hour
- **Number of ensembles:** 32
- **Hurricane Fred (2009)**
- **No bias correction** (advantage of clear-sky GSI correction not obvious)
- To be submitted for publication by M. Zhang et al.

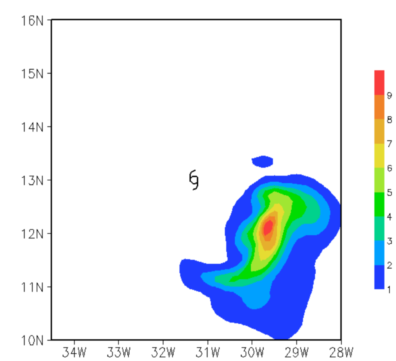
Hurricane Fred (2009): Analysis

Total cloud condensate (cwm)
Valid 0600 UTC 9 Sep 2009

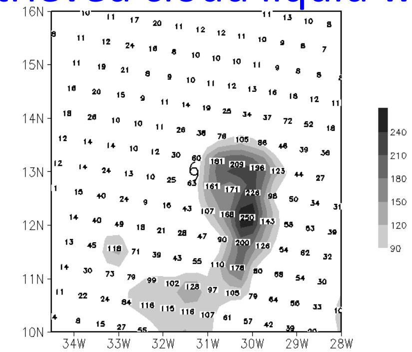
Control experiment



All-sky radiance assimilation



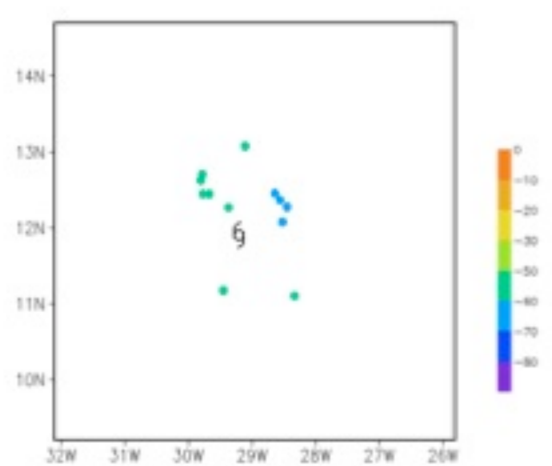
Verification: AMSU-A NOAA-16 retrieved cloud liquid water



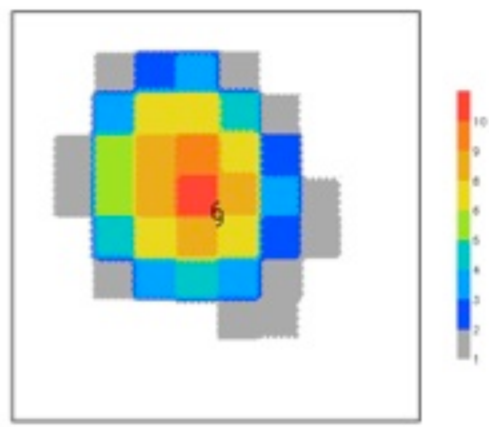
Assimilation of all-sky infrared radiance is able to improve clouds in TC core

Hurricane Fred (2009): All-sky SEVIRI information content (DFS)

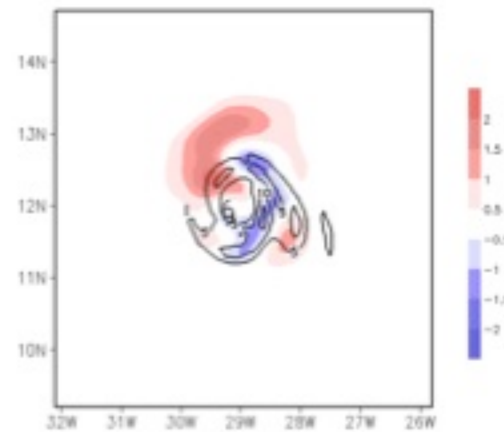
Tb observations



Degrees of Freedom for Signal



Total cloud condensate (cwm)



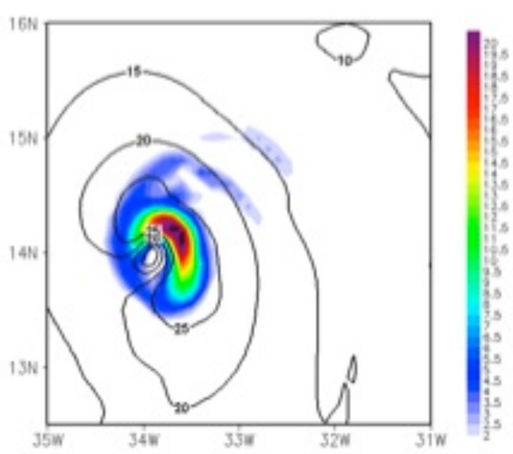
Valid 1800 UTC 08 Sep 2009

SEVIRI infrared cloudy radiance observations adds new information

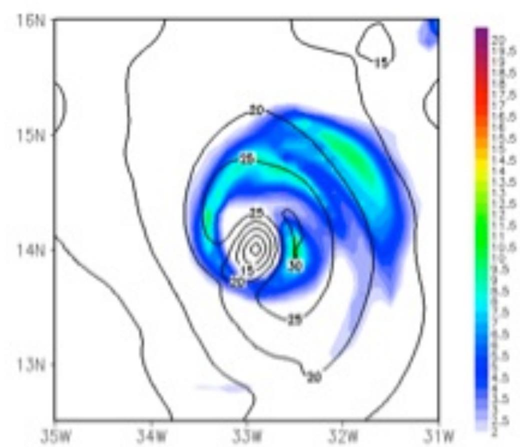
Hurricane Fred (2009): 21-hour forecast

Total cloud condensate (cwm)
Valid 0300 UTC 10 Sep 2009

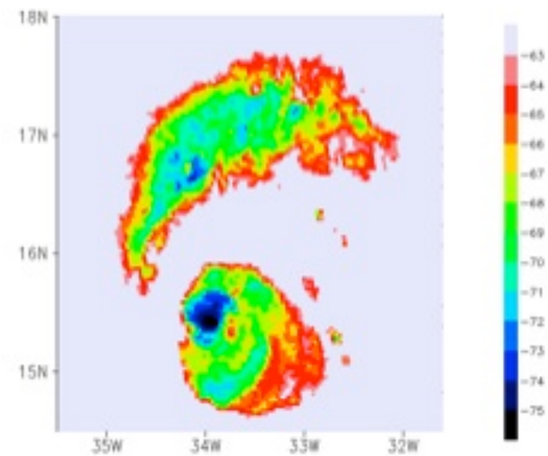
Control experiment



All-sky radiance assimilation



Verification: Seviri radiance observations

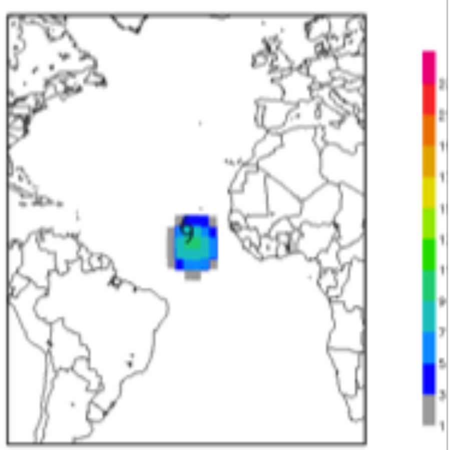


Assimilation of all-sky infrared radiance improves the forecast of clouds in TC core area

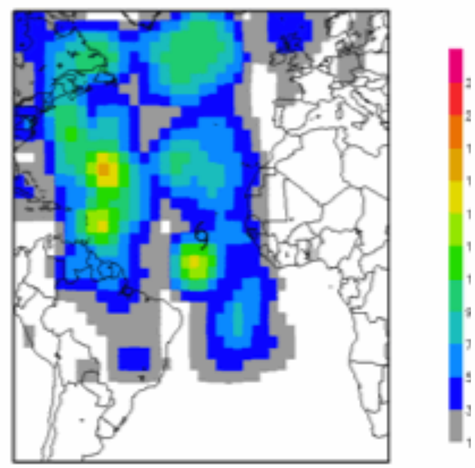
Hurricane Fred (2009): Assimilation of all-sky SEVIRI and AIRS SFOV (q,T) in HWRF outer domain

Information content - DFS

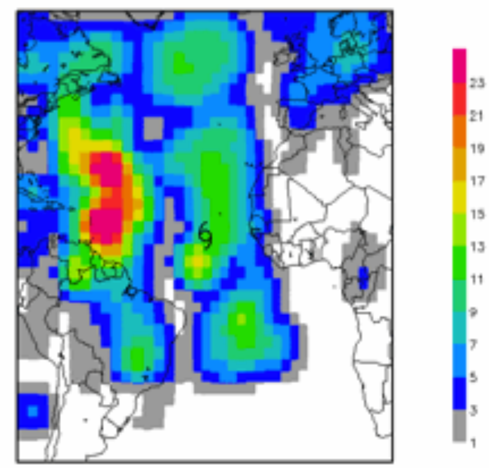
MSG SEVIRI only



MSG SEVIRI and AIRS q profile



MSG SEVIRI and AIRS T profile



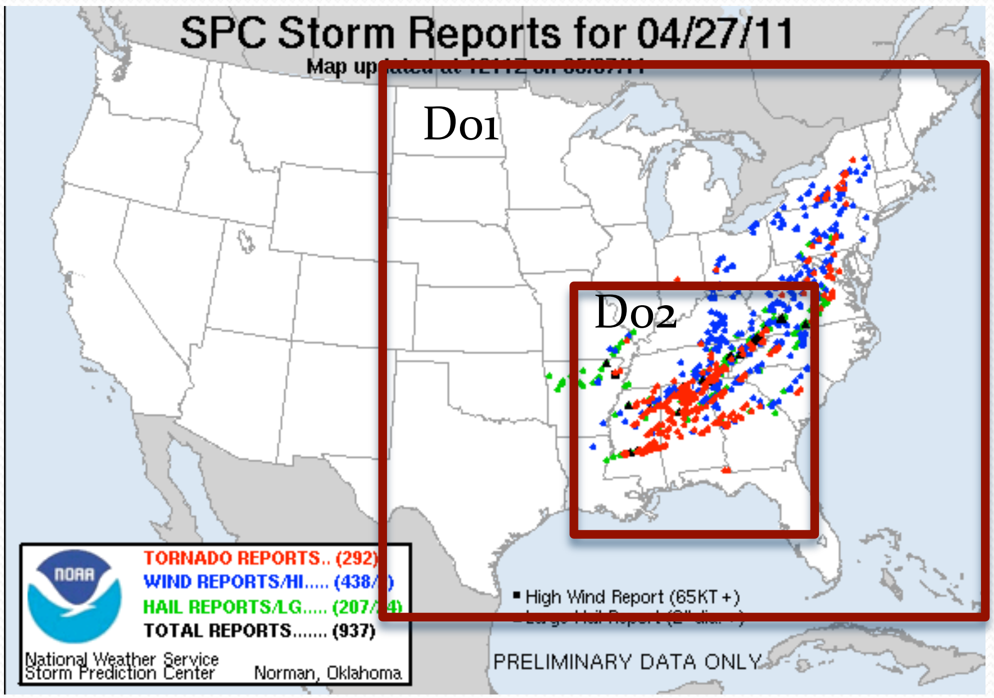
In outer domain (with less clouds) DFS shows more benefit from AIRS SFOV temperature data than from specific humidity data

Lightning data assimilation: Severe weather applications

- **Model:** NOAA WRF-NMM (27km/9km)
- **Results for the inner nest at 9 km resolution**
- **Observations:** WWLLN [proxy for GOES-R GLM)
- **Data assimilation interval:** 6 hours
- **Number of ensembles:** 32
- **Tornado outbreak over Southeast US in April 2011**
- From Apodaca et al. (2013)

Severe weather outbreak over the southeastern US on April 25-18, 2011

Model domain and tornado reports for April 27, 2011



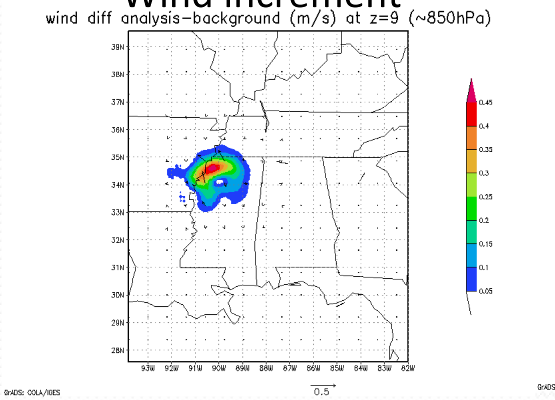
Lightning observation operator

- **WWLLN can observe only cloud-to-ground (C-G) flashes**
- **Regression between lightning flash rate and model variables**
  - Best regression suggests cloud ice and vertical graupel flux (McCaul et al. 2009)
- **WRF-NMM microphysics (Ferrier) does not predict cloud ice:**
  - Need to rely on less accurate regression: maximum vertical updraft
- **Present:**
  - Use max vertical updraft and WWLLN
- **Future:**
  - Include more complex microphysics to improve obs operator
  - Use better GLM proxy observations (C-G and intra-cloud)
  - Increase the resolution to 1-3 km

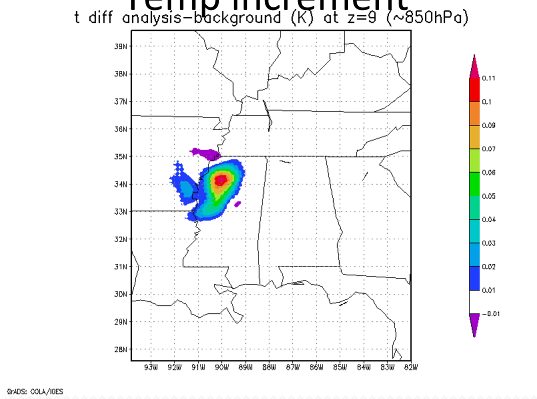
Lightning data assimilation with MLEF: Single observation experiment

Analysis response to a single observation of flash rate in a 6-hour interval

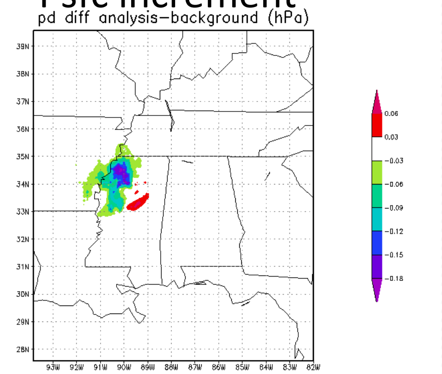
Wind increment



Temp increment

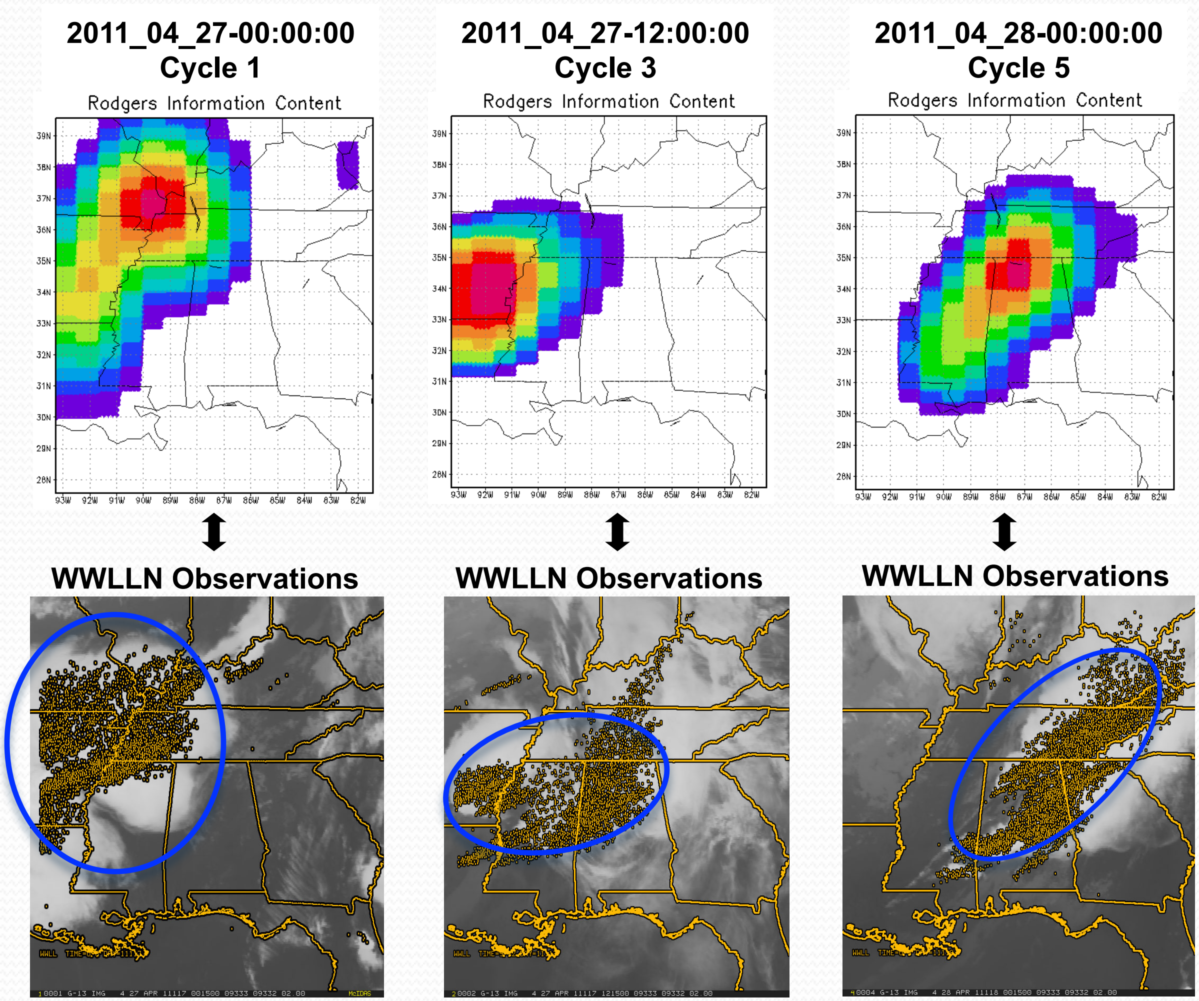


Psfc increment



Assimilation of lightning observations impacts all model variables and improves storm environment conditions

Information content of lightning observations: DFS

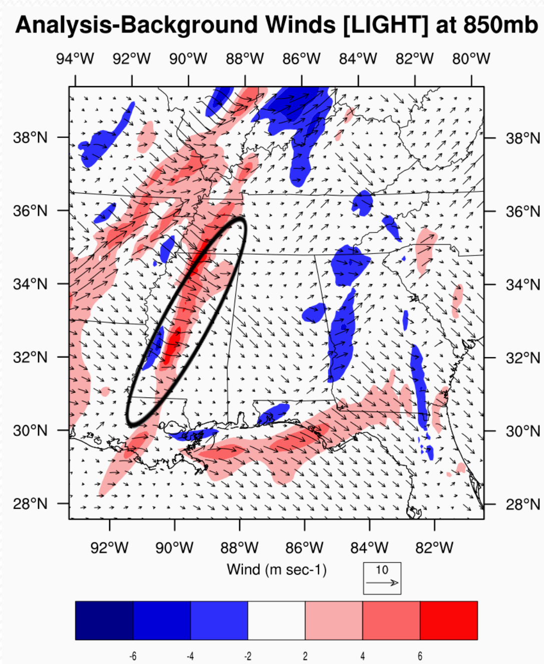


Time and flow dependent information added by assimilating lightning data

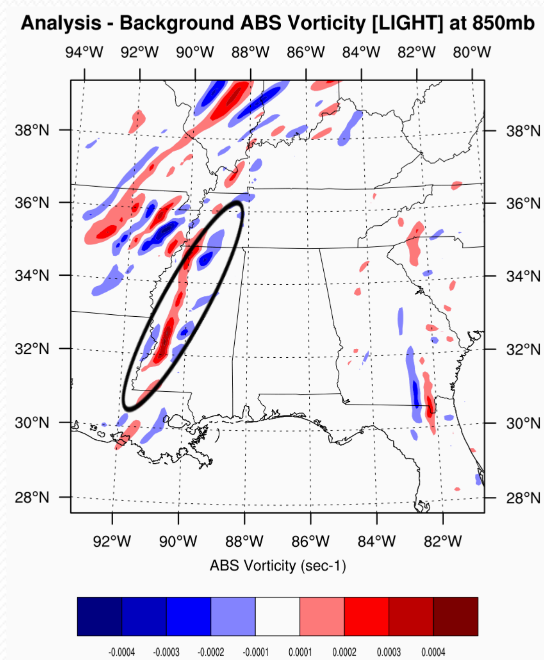
Impact on storm environment

Analysis increments: $x^a - x^f$

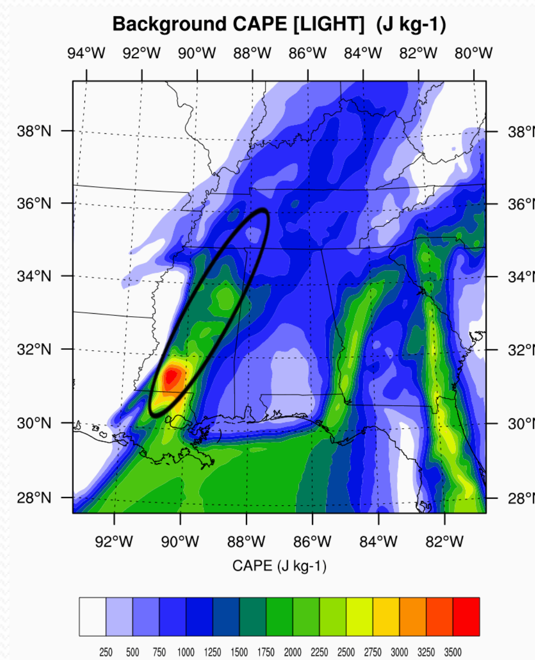
Wind increment at 850 hPa
Valid 04/28 at 00UTC



Vorticity increment at 850 hPa
Valid 04/28 at 00UTC



Background CAPE
Valid 04/28 at 00UTC



Lightning data assimilation increases the advection of low-level vorticity into the region of large CAPE

New direction: High-impact weather

- **Combine all observations in applications to TC/severe weather:**
  - All-sky infrared radiances(GOES-R ABI)
  - Lightning (GOES-R GLM)
  - All-sky microwave radiances
  - AIRS/IASI (sounder)
  - NOAA operational observations (GSI)

- **Examine the impact of WV channels for TC genesis**

- **Assess the value of combined observations in regional hybrid GSI**

New directions: Coupled models

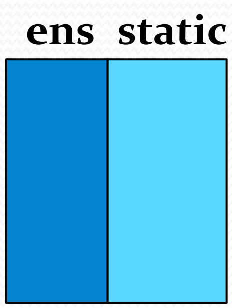
- **Extend utility of GOES-R data to chemistry:**
- Improve predictions of high-impact weather **and** air-quality
- WRF-CHEM model: coupled atmosphere-chemistry
- All-sky ABI radiances and GLM flash rates contain a valuable information about NOx, O_3, and aerosols

- **Extend utility of GOES-R data to land-surface and coastal ocean**
- Focus on improving predictions of hurricane landfall, storm surge
- coupled atmosphere-ocean-land-hydrology model
- add ocean observations (HF radar, Lagrangian data, altimeter, satellite)

New directions: Hybrid DA

- **Extend MLEF to include static/variational and ensemble error covariances**
  - Hybrid ensemble-variational error covariance
  - A single DA system (no separate variational and ensemble algorithms)
  - Maintain optimal Hessian preconditioning (e.g., observation component)
  - Requirement: Approximate variational covariance

$$P_f^{1/2} = \left[\; P_{ens}^{1/2} \quad P_{SR}^{1/2} \; \right] =$$

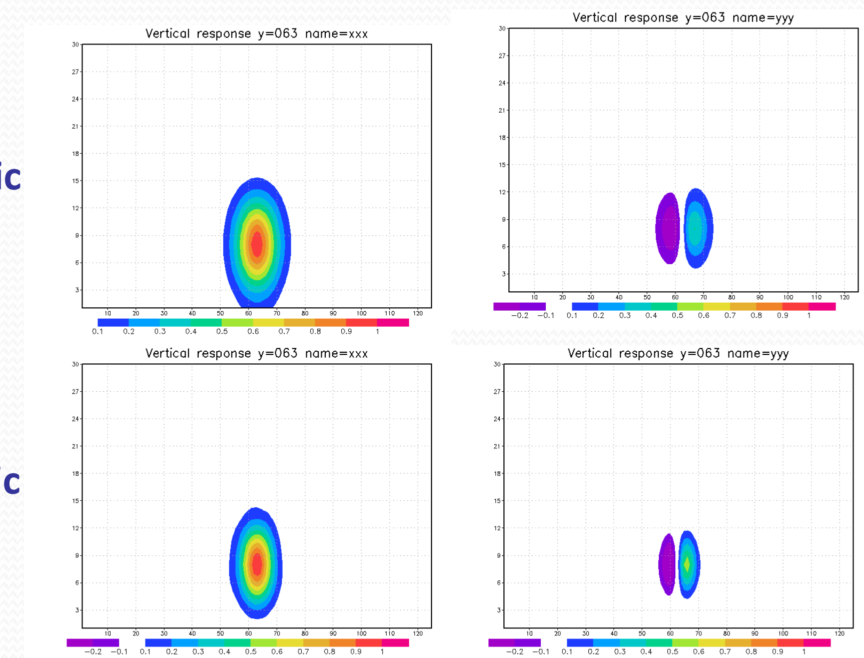


Variable 1

Variable 2

True static

MLEF static



- Improve robustness of the system
- Efficient use of all observations

Future

- **Continue high-impact weather DA applications**

  - Increase resolution to 1-3 km

  - Assimilate all available observations

- **Prepare for GOES-R launch**

  - simultaneous assimilation of ABI and GLM

  - use GSI/hybrid GSI as a framework to access observations

- **Expand applications to chemistry, land-surface, carbon, ocean**

  - important new applications

  - extend the utility of GOES-R data

- **Further development of hybrid variational-ensemble systems**

  - hybrid forecast error covariance with optimal Hessian preconditioning

Thank you!

References:

Apodaca, K., M. Zupanski, M. DeMaria, J. Knaff, and L. Grasso, 2013: Evaluating the potential impact of assimilating satellite lightning data utilizing hybrid (variational-ensemble) methods. Submitted to *Tellus*.

McCaul, E. W.,K. M. LaCasse, and D. J. Cecil, 2009: Forecasting lightning threat using cloud-resolving model simulations. *Wea. Forecastin*g, 24, 709-729.

Steward, J. L., I. M. Navon, M. Zupanski, and N. Karmitsa, 2012: Impact of Non-Smooth Observation Operators on Variational and Sequential Data Assimilation for a Limited-Area Shallow-Water Equation Model. *Quart. J. Roy. Meteorol. Soc*., **138**, 323-339.

Zhang, M., M. Zupanski, M.-J. Kim, and J. Knaff, 2013: Assimilating AMSU-A Radiances in TC Core Area with NOAA Operational HWRF (2011) and a Hybrid Data Assimilation System: Danielle (2010). *Mon. Wea. Rev*., in print.

Zhang, S. Q., M. Zupanski, A. Y. Hou, X. Lin, and S. H. Cheung, 2012: Assimilation of precipitation-affected radiances in a cloud-resolving WRF ensemble data assimilation system. *Mon. Wea. Rev*., **141**, 754-772.

Zupanski D., M. Zupanski, L. D. Grasso, R. Brummer, I. Jankov, D. Lindsey and M. Sengupta, and M. DeMaria, 2011: Assimilating synthetic GOES-R radiances in cloudy conditions using an ensemble-based method. *Int. J. Remote Sensing*, **32**, 9637-9659.

Zupanski, D., S. Q. Zhang, M. Zupanski, A. Y. Hou, and S. H. Cheung, 2011: A prototype WRF-based ensemble data assimilation system for downscaling satellite precipitation observations. *J. Hydromet*., **12**, 118-134.

Zupanski, M., 2005: Maximum Likelihood Ensemble Filter: Theoretical Aspects. *Mon. Wea. Rev*., **133**, 1710–1726.

Zupanski, M., I. M. Navon, and D. Zupanski 2008: The maximum likelihood ensemble filter as a non-differentiable minimization algorithm. *Q. J. Roy. Meteor. Soc*. 134, 1039-1050.

Zupanski M., 2013: All-sky satellite radiance data assimilation: Methodology and Challenges. *Data Assimilation for Atmospheric, Oceanic, and Hydrologic Applications*, S.-K. Park and L. Xu, Eds, Springer-Verlag Berlin, in print.

[https://www.cira.colostate.edu/projects/ensemble/index.php]